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METHODS FOR CONTINUOUS IMPROVEMENT OF FIELDED JET ENGINE RELIABILITY AND MAINTAINABILITY

by

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December, 1994

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METHODS FOR CONTINUOUS IMPROVEMENT OF FIELDED JET ENGINE RELIABILITY AND MAINTAINABILITY

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TABLE OF CONTENTS

List of Abbreviations

A_a	Achieved Availability
A_i	Inherent Availability
A_o	Operational Availability
BCM	Beyond the Capability of Maintenance
COPES	Control Program For Engineering Synthesis
CPI	Continuous Process Improvement
DBMS	Data Base Management System
ERAP	Engine Reliability Analysis Program
FOM	Figures Of Merit
LCC	Life Cycle Cost
LSA	Logistics Support Analysis
M	Mean Active Maintenance Time
M_{ct}	Mean Corrective Maintenance Time
M_{pt}	Mean Preventive Maintenance Time
MDT	Mean Down Time
MTBF	Mean Time Between Failure
MTBMAF	Mean Time Between Mission Affecting Failures
MTBR	Mean Time Between Repair
MTTR	Mean Time To Repair
NADEP	Naval Aviation Depot
NALDA	Naval Aviation Logistics Data Analysis
NAMO	Naval Aviation Maintenance Office
NAST	Naval Aviation Systems Team
RMA(t_0)	Engine Reliability (time Zero)
RAP	Reliability Analysis Program
RCM	Reliability Centered Maintenance
T/M/S	Type/Model/Series
TSN	Time Since New
WUC	Work Unit Code

I. INTRODUCTION

A. BACKGROUND

The use of Continuous Process Improvement (CPI) methods have gained acceptance within industries throughout the world. Most notably, Japanese industries have employed the now familiar Deming Cycle (Plan, Do, Check, Act) with great success. The CPI method follows a clear, step-by-step approach to improving the processes used to produce products, thereby improving quality. Customers view quality in six dimensions: (1) operation, (2) reliability/durability, (3) conformance, (4) serviceability, (5) appearance, and (6) perceived quality/reputation. (Heizer, 1993).

Rather than merely adhering to specifications, which are basically go/no go criteria, CPI methodology seeks to continuously reduce process variability or other quality indicies, such that the end product quality meets or exceeds customer expectations (Figure 1).

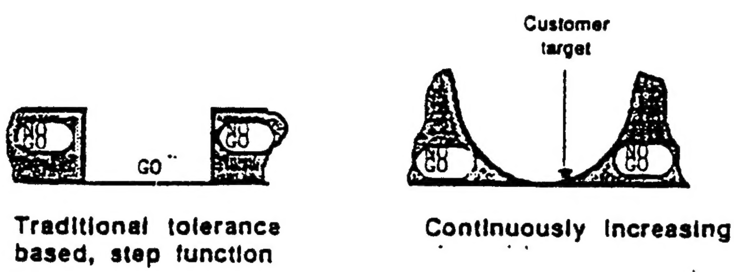

Figure 1. Tolerance limit versus continuous improvement (From Ref. Messina, 1987).

The CPI concepts can also be applied to the performance of fielded jet engines through the analysis of existing databases such as the Naval Aviation Logistics Data Analysis

(NALDA) database. The identification of potential areas for improvement based upon Pareto principles allows planners to identify those areas where the greatest amount of performance improvement (marginal gain) can be achieved per dollar expended (marginal cost). The major Pareto principle states that a small percent of the components of a system or process frequently cause a large percent of the system or process failures.

The current NALDA database includes the accumulation of eighteen months of data. It is detailed by engine type/model/series. The first step in our methodology is to determine the life cycle curve for the TF-34 so that the mature stage can be identified. Discussions with Mr. Paul Zimmerman, Naval Air Systems Team, Code 4431, lead us to the conclusion that engines maintained under the Reliability Centered Maintenance (RCM) concept are, on average, the equivalent of mature engines and are therefore comparable to one another. However, this has not been statistically verified in this thesis.

Under the RCM concept, engines are continuously renewed through the replacement of life limited components based upon hours of operation. Operating hours or age data from engines that are continuously renewed in this fashion is not good data for estimating the mean time between failure.

Engines that are not maintained under the RCM concept should first be analyzed using Time Since New (TSN) versus failure rate so that engines in their mature stage can be segregated from all others. Many complex systems in their mature stage are characterized by a constant/stable failure rate.

Comparing the failure rate versus TSN (Figure 2) will indicate graphically which engines belong to the population of mature systems. Failure to segregate mature engines from the population of engines may skew the results.

Figures of merit (FOM) are selected that will be used to establish the baseline (current status) of an engine system in terms of the parameters that make up the FOM. Examples of three common FOM's include: mean time between failure (MTBF), mean time to repair (MTTR), and inherent availability (A_i). Other FOM's can also be accommodated and calculated from data contained in NALDA and in the Reliability Analysis Program (RAP) reports.

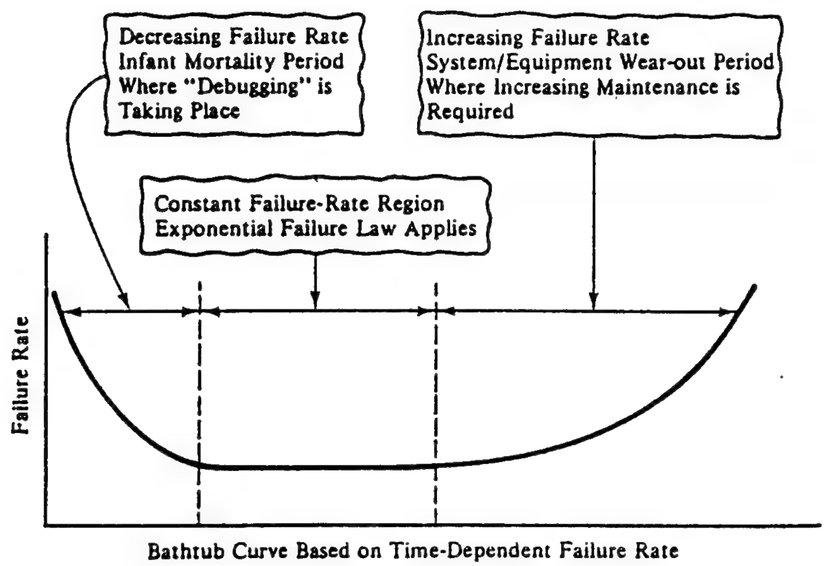

Figure 2. Bathtub Curve (From Ref. Blanchard, 1992).

Once the baseline values have been established, we can compare them with a standard or a benchmark value as a reference point. This aids analysts and program managers in answering the question, "Do the RAP reports indicate acceptable or unacceptable performance?"

Improvement of FOM values is a multi-step process. The continuous process improvement approach is used to do this.

It begins with a focus on the critical few failure causes, identified by Pareto analysis, that are impacting the system. These critical few failure causes are associated with those engine components or subsystems with the highest failure rate that result in the aircraft being unable to perform its mission due to engine failure. Identifying these components by failure rate will indicate where the greatest amount of improvement in the FOM values can be achieved.

Factors such as engine unscheduled removals, cannibalization rates, and infant mortality are some of the measures closely tracked through standard RAP reports. These measures aid program managers in monitoring the overall health of an engine system on a macro level. These RAP measures should indicate to the program manager the effectiveness of changes implemented through the CPI approach. The determination of baseline values for the selected FOM's and the determination of the Pareto items are the micro level tasks required at the analyst level.

The use of structured CPI methods should show that a standardized method for improving jet engine reliability and maintainability figures of merit can be established. The intent in this is to develop a method based upon proven and relatively simple statistical techniques that can be applied to any fielded jet engine.

B. OBJECTIVES

The primary objectives of this thesis are as follows:

- Develop a standardized and user friendly methodology to facilitate the systematic improvement of fielded jet engine reliability and maintainability.

- Demonstrate a method for establishing baseline jet engine logistics performance using selected FOM criteria.

- Demonstrate the application of commercially available software to create frequency distributions and statistically analyze NALDA data.

- Demonstrate the use of the Pareto principles as a tool that facilitates effective improvement in jet engine reliability and maintainability.

C. RESEARCH QUESTIONS

The overall guiding questions are as follows:

- What methods and criteria can be used effectively for establishing operational jet engine reliability and maintainability targets, goals or benchmarks?

- Can operational jet engine maintainability and reliability goals be established using information contained in the RAP report alone?

D. SCOPE, LIMITATIONS, AND ASSUMPTIONS

The scope of the research was limited to the TF-34 as a case example due its use as the model for the development of the Reliability Analysis Program (RAP).

The number of figures of merit (FOM) was limited to three for demonstration purposes. Other FOM values can be calculated and compared using similar methodologies.

The authors assumed the readers understanding of basic statistics, familiarity with NALDA data and the Reliability Analysis Program, and experience with spreadsheet software programs such as EXCEL or LOTUS.

E. THESIS PREVIEW

The Navy currently collects data on all jet engines through the use of programs such as the following:

- Maintenance Data System (MDS), which includes the Visual Information Display System/Maintenance Action

Form or VIDS/MAF

- Naval Aviation Logistics Command Information System (NALCOMIS)
- Aircraft Engine Management System (AEMS)
- Depot Maintenance Data System (DMDS)
- Technical Directive Status Accounting System (TDSA)
- Master Index of Repairables (MIR)
- Engine Composite and Tracking (ECOMTRAK)
- Engineering Change Proposal, Tracking and Evaluation (ECP-TRAK)
- Naval Flight Information Record (NAVFLIR)

The data from these sources of logistics information are collected from all three levels of maintenance organizational, intermediate and depot. The recording of daily maintenance and management data is very thorough and detailed. It includes such information as work unit code, type maintenance code, serial numbers, hours, cycles, failure codes, unit identification codes, status codes and other information. This information is eventually compiled and transmitted to the Naval Aviation Maintenance Office (NAMO). Access to the data is available to researchers, managers and end users through the Naval Aviation Logistics Data Analysis system or NALDA.

In terms of NALDA database accuracy, a previous Naval Postgraduate School graduate had the following to say:

> The [NALDA] data in this thesis [Baldwin's] was checked using the MDS and AEMS databases and was found to be extremely accurate. (Baldwin, 1992).

The process used to query the NALDA database, however, is not user friendly and requires a two-week course of instruction before users are allowed to access the system.

Downloading and interpretation of specific reports can be a lengthy process. However, acquiring a data file copy of desired parameters can be accomplished quickly and easily with the assistance of a NALDA trained data analyst. Data can then be transmitted via MILNET or INTERNET to anyone with a computer mailing address. This process was used by the authors to obtain TF-34 data from NADEP Alameda, California, which was transmitted to their computer mail accounts at NPS Monterey, California. The data file transmission, decoding and importing procedure required one phone call and about 30 minutes of computer time (Figure 3).

•	SERNO	FHRS-N	FHRS-RPR	FHRS-INST	FHRS-REM	UIC	STATUS-S	REASON	REMOVE	START-YY	START-DA	ETR-NUM		FHRS-N	REASON
•	2020	1802	283	283	283	9298	2474	1	Z	8811	88319	55		1802	1
•	2022	1868	619	619	619	9353	2474	1	Z	8905	89140	62		1868	1
•	2024	1873	686	316	316	9739	2474	1	W	8910	89278	70		1873	1
•	2024	1921	48	48	48	52947	2474	1	W	9001	90021	86		1921	1
•	2011	1925	1121	9	9	9539	2474	1	Z	8903	89060	23		1925	1
•	2011	2360	959	374	374	9263	2474	1	G	9106	91180	57		2360	1
•	2011	2530	170	170	170	9298	2474	1	Z	9203	92086	69		2530	1
•	2020	2562	251	251	251	9287	2474	1	Z	9309	93270	115		2562	1
•	2022	2598	92	92	92	9572	2474	1	Z	8810	88287	72		2598	1
•	2022	2794	154	154	154	9298	2474	1	Z	8811	88333	88		2794	1
•	2023	2820	1	1	1	9287	2474	1	Z	8906	89179	92		2820	1
•	2021	2897	507	507	507	9263	2474	1	W	8906	89169	55		2897	1
•	2022	2913	315	315	315	9287	2474	1	Z	9001	90011	85		2913	1
•	2023	2961	238	238	238	9226	2474	1	Z	8907	89208	115		2961	1
•	2020	2976	99	99	99	9298	2474	1	Z	9207	92199	104		2976	1
•	2022	3098	304	304	304	9298	2474	1	Z	8911	89307	96		3098	1
•	2023	3159	1171	20	20	9646	2474	1	Z	8811	88327	90		3159	1
•	2021	3214	78	78	78	9287	2474	1	Z	8908	89219	176		3214	1
•	2023	3295	484	484	484	9353	2474	1	W	9001	90018	101		3295	1
•	2020	3297	82	80	82	9739	2474	1	W	9202	92051	106		3297	1
•	2023	3304	290	19	19	9353	2474	1	Z	9006	90155	176		3304	1
•	2021	3377	161	161	161	9298	2474	1	Z	8906	89174	152		3377	1
•	2023	3383	113	113	113	8629	2474	1	Z	9001	90007	162		3383	1
•	2020	3437	376	376	376	8629	2474	1	Z	9101	91029	75		3437	1
•	2022	3448	679	221	221	9539	2474	1	Z	9007	90210	211		3448	1
•	2020	3475	228	228	228	9629	2474	1	G	9106	91164	75		3475	1
•	2020	3512	210	210	210	9345	2474	1	W	9302	93043	69		3512	1
•	2022	3557	339	339	339	9629	2474	1	G	9104	91095	106		3557	1
•	2020	3566	942	20	20	9298	2474	1	Z	9010	90289	54		3566	1
•	2020	3567	688	688	688	9263	2474	1	Z	9005	90127	93		3567	1
•	2021	3573	55	55	55	52947	2474	1	W	9104	91114	134		3573	1
•	2022	3625	676	676	676	9192	2474	1	Z	8903	89083	160		3625	1
•	2020	3632	390	231	231	9629	2474	1	Z	8908	89213	138		3632	1
•	2024	3635	830	277	277	9353	2474	1	Z	9108	91226	127		3635	1
•	2020	3716	20	8	20	55600	2474	1	Z	8901	89015	153		3716	1

Figure 3. Example of NALDA data file imported to EXCEL.

Through the use of commercially available spreadsheet programs such as EXCEL or LOTUS, data can be sorted by any parameter contained in the database such as: serial number, time since new, flight hours between repairs, unit identification code, etc. Rapid statistical calculations and graphics allow interactive analysis of the data through sub-programs built into the spreadsheet programs. As mentioned earlier, an important first step for those engine type/model/series not maintained under the RCM concept is to identify the mature stage of the system life cycle. The life cycle curve is the inverse of the "bathtub" curve of reliability. The "bathtub" curve is the failure rate function. It depicts a decreasing failure rate in the early stages of the system, a constant failure rate during the mature stage, and an increasing failure rate, primarily due to wear-out, in the decline stage. Failure to identify the mature stage engines will result in the mixing of engines that are statistically different in their operating characteristics, specifically, their MTBF or failure rate.

The data required from NALDA to produce the failure rate function is TSN (age in hours) and the failure rate times. With this data, EXCEL can quickly plot the failure rate function. That portion of the curve that indicates a constant failure rate versus age (TSN) defines those engines which are mature. The Time-To-Failure of engines in the mature stage typically has an exponential distribution. In this case the reliability function is defined by the equation:

$$R(t)=e^{-\lambda t}. \tag{1}$$

II. STATISTICAL ANALYSIS OF LIFE DATA

A. METHODOLOGY

The following discussion outlines the procedures for one application of a CPI approach using basic statistical techniques. This systematic approach can be applied to any engine type, model, series:

1. Calculation of the Time-To-Failure Frequency Distribution

a. MTBF Defined

The failure rate $\lambda(t)$ is a measure of the rate at which engines are failing that have operated for a time (t). A failure is defined as an instance when the system is not operating within a specified set of parameters. If $\lambda(t)$ is a constant, say λ, then the time to failure distribution has an exponential distribution. In this case the MTBF = $1/\lambda$ and the MTBF is a measure of reliability. MTBF is always the average time between failures and can be estimated by the ratio of total operating time on all engines to the number of those engines that have failed. Typically the failure rate is constant for engines in the mature stage when wear-out is not a factor. Consequently the exponential distribution applies in this case.

b. Step by Step Procedure for Time-To-Failure Data

The following procedure can be used for constructing Time-To-Failure frequency distributions. Any spreadsheet software program with graphics and statistical capabilities can be used. The authors chose EXCEL. (Appendix A, Table II).

Step 1: Query the NALDA database for data on hours of operation before failure (time between failure). Do not confuse *mean time* between failure with *time* between failure! Use of all available data points is recommended.

Step 2: If necessary the data can be transmitted as an attachment to remote users via INTERNET or MILNET, otherwise a disk copy of the data can be forwarded.

Step 3: Decode the data if necessary, and import it into any spreadsheet program such as EXCEL, LOTUS, or the interactive version of ERAP when it becomes available. Graphics and statistical capabilities are required.

Step 4: Sort the data, low to high, in one column. Highlight the column of data and have the software program produce a frequency distribution. The procedures for doing this will vary depending on the software you are using. A histogram of the data can be plotted with virtually any spreadsheet or statistical software program. Class intervals are usually automatically selected, but may need to be adjusted in order to get a clearer picture of the distribution type.

Step 5: Highlight the column of data again, and select "descriptive statistics." This step will produce the mean (MTBF), median, mode, range and standard deviation values for the distribution.

Step 6: Add three additional columns labeled failure rate, number of units surviving, and reliability. The column labeled "Units Surviving" is calculated by subtracting the number of failures that occurred from the total number of units (or total number of data points). The column labeled "Failure Rate" is calculated by dividing the number of

failures in each interval by the product of the life in hours (operating time) times the units surviving. (See Appendix B, Table II). The column labeled "Reliability" is calculated by dividing the number of units surviving by the total number of units.

Step 7: Highlight the column of data containing the life in hours and failure rate and graph the data on an "X-Y" chart and observe the type of distribution formed. Again highlight the life in hours data and the reliability data and graph the data as before. This produces a graph of the reliability function. The analyst can now make statistical estimates of selected FOM items including the following:

- MTBF
- Percentiles of the Time-To-Failure distribution
- Failure rate as a function of operating time
- Distribution Parameters of the Time-To-Failure distribution
- Expected number of failures based on operating level (funded flight hours for example).

The frequency distribution allows the analyst to determine the type of Time-To-Failure distribution to use for developing statistical confidence intervals for the MTBF and reliability of an engine type/model/series using existing confidence interval estimation procedures.

2. Calculation of the Time-To-Repair Frequency Distribution

The procedure for obtaining a data file and producing a frequency distribution for Time-To-Repair data is similar to that used for Time-To-Failure data. It is restated for continuity purposes and to highlight the Time-To-Repair sample data definition that the analyst conducting the NALDA query will need to know.

a. MTTR Defined

Each time a system fails, a series of steps must be performed to correct the discrepancy. These steps include: detection, isolation, disassembly to gain access, repair, reassembly, and test/check. Completion of these steps constitutes a corrective maintenance cycle.

By taking a random sample of corrective maintenance cycles we can build a frequency distribution that will allow the analyst to estimate the population MTTR and related FOM elements.

b. Step by Step Procedure for Time-To-Repair Data

The following procedure can be used to compute and graph Time-To-Repair FOM elements for any engine type/model/series:

Step 1: Query the NALDA database for corrective maintenance cycle times as defined previously. These times may be measured at the organizational, intermediate or depot level of maintenance, depending on what level of maintenance is being analyzed.

Step 2: As with the Time-To-Failure data file, the Time-To-Repair data can be transmitted to remote users via MILNET or INTERNET, or otherwise forwarded as a disk copy.

Step 3: Decode the data if necessary, and import it into any spreadsheet program or the interactive version of ERAP.

Step 4: Sort the data, low to high, in one column. Highlight the column of data and have the software program produce a frequency distribution. (The procedures for doing this will vary depending on the software you are using). A histogram of the data can be plotted with virtually any spreadsheet or statistical software program. Class intervals or bin ranges are usually automatically selected, but may need to be adjusted in order to get a clearer picture of the distribution type.

Step 5: Highlight the column of data again, and select "descriptive statistics." This step will produce the mean (MTTR), median, mode, range and standard deviation values for the distribution. As with the Time-To-Failure distribution, the analyst can now make statistical estimates of MTTR and related FOM elements.

3. Inherent Availability Calculation

Inherent Availability is a function of MTBF and MTTR, and is often calculated using the following equation:

$$A_I = \frac{MTBF}{MTBF + MTTR} \quad (2)$$

Inherent Availability is the probability that a system or equipment, when used under stated conditions in an *ideal* support environment (i.e., readily available tools, spares,

maintenance personnel, etc.), will operate satisfactorily at any point in time as required. It usually excludes preventive or scheduled maintenance actions, logistics delay time, and administrative delay time.

B. INTERPRETATION OF MTBF AND MTTR FIGURES OF MERIT

Once the values for MTBF and MTTR (and any other desired FOM's) have been calculated they can be compared with desired or specified values to identify possible areas for improvement. However, the analyst will still not have answered the question, "Are these values acceptable or not acceptable?" Some researchers recommend a comparison using ratios (percentages) of the calculated FOM values with (1) those FOM values originally specified during the concept development stage (these should be contained in the Logistics Support Analysis Record or LSAR), or (2) a benchmark value calculated from a specified percentile of the distributions developed previously. See Section B.2 of chapter IV for more details on benchmarking. A simple ratio of the actual values to the specified values provides one method of determining whether current maintainability and reliability parameters are above or below specifications.

The procedure is similar for any other parameter the analyst or program manager desires to measure, including the following:

- Mean Down Time (MDT)
- Mean Time Between Replacement (MTBR)
- Mean Active Maintenance Time (M)
- Achieved Availability (A_a)

- Operational Availability (A_o)
- Mean Corrective Maintenance Time (M_{ct})
- Mean Preventive Maintenance Time (M_{pt})

This systematic approach to analyzing NALDA data allows Program Managers and Data Analysts to accomplish three important objectives: (1) establish where the system is now in terms of MTBF, MTTR, A_i, and other FOM values, (2) measure the current FOM values against those which were originally specified or with a benchmark value, and (3) measure the effect of any changes made to improve the engine, by monitoring their effect on selected FOM values.

III. PERFORMANCE GOAL SETTING

A. PREFERRED APPROACH

The preferred time for establishing figures of merit (FOM) and effectiveness measures such as Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), Inherent Availability and others, is during the Systems Maintenance Concept Development Stage. The maintenance concept is defined at program inception and is a prerequisite to system/product design and development. The maintenance concept is also a required input to logistics support analysis (LSA).

When FOM values have been established prior to engine design and production, the most logical measure of whether the Reliability Analysis Program data indicates acceptable or unacceptable performance, would be to compare the actual FOM's with those specified in the contract/ LSA. The minimum acceptable performance might be that which was specified.

The FOM's and effectiveness measures are computed during the concept phase of systems development. The trade-offs between reliability and maintainability must be considered in terms of their effect on cost and availability. The optimum cost allocation approach (Figure 4) is one method for defining the appropriate mix of MTBF and MTTR values (Anderson, March 1976). However, this method requires cost functions which are usually not available. Numerous trade-off analysis methods are defined in contractor and DOD documents.

Engine systems developed under the life cycle approach should have values for various FOM's available through the Logistics Support Analysis Record (LSAR). The NALDA database and RAP reports can then provide an excellent source of data for comparing what was contracted for, and what is actually occurring. If the RAP reports show that the values for MTBF, MTTR, Availability, etc., are below those values specified in

the LSAR, analysts may be able to conduct further interactive analysis of the database using existing commercial off-the-shelf software to identify possible component or subsystem failure causes. This might begin with a form of sensitivity analysis where the NALDA database is used to correlate a particular component problem to a potential common source such as an AIMD, Depot facility, or operating environment. If such a correlation is found, additional field level research may be necessary to get to the route cause of the failures. Some factors that can influence the reliability of a component may not be detectable through the NALDA database alone, such as; maintenance policy or procedures, support equipment out of calibration, manufacturing equipment variability, etc. Effective use of the NALDA database should significantly narrow the search.

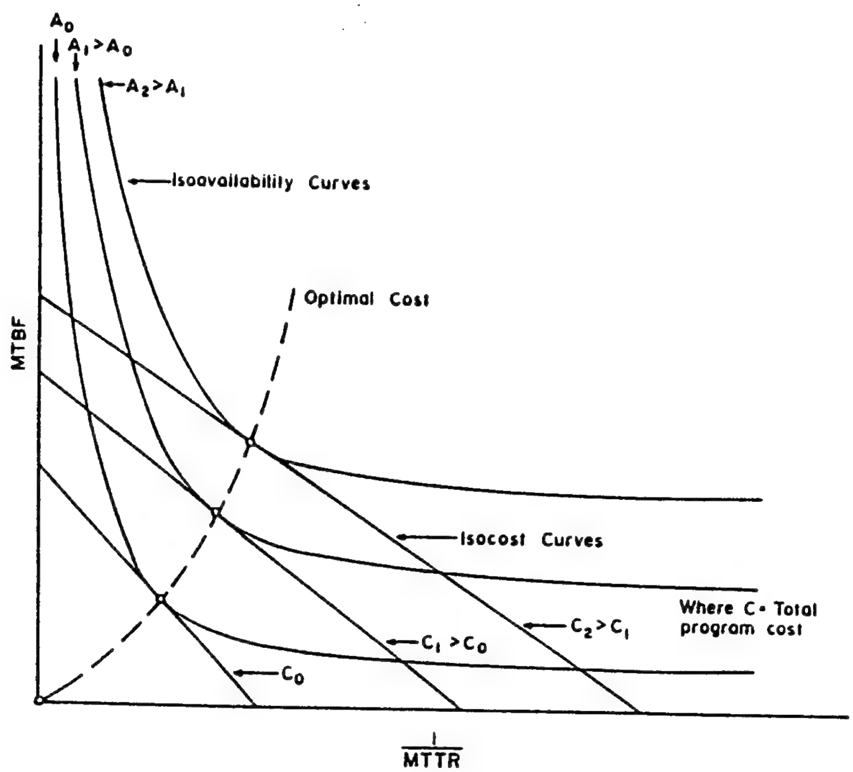

Figure 4. Optimum Cost Allocation between MTBF and MTTR (From Ref. Anderson, March 1976).

B. MISSING DATA SPECIAL CASE

1. Reconstruction

The TF-34 was designed and developed before the implementation of the Systems Approach and Logistics Support Analysis concepts in Defense Acquisition Programs. As a result, the basic concepts described in the preceding section cannot be applied directly to the TF-34. Although General Electric has historical data (Duane Curves for reliability growth analysis) that might be used to determine FOM values for the TF-34 based upon the original design criteria, time constraints prevented research in this area.

Reconstruction of the MTBF, MTTR and Isoavailability Curves for the TF-34 would allow an analysis of what the optimum cost allocation values should be. This would require an analysis of the cost versus reliability tradeoff, and cost versus maintainability tradeoff as shown in Figures 5 and 6 (Anderson, March 1976). These figures could then be compared as described before, with the NALDA database and RAP to determine where the system performance lies in comparison with those FOM values calculated from the reconstruction of contractor data. This may be a subject for additional research.

2. Benchmarking

An interim step that can be applied to any engine system lacking pre-established FOM's, is one known as Benchmarking. Benchmarking involves selecting a demonstrated standard of performance that represents the very best performance for processes or activities (Heizer, 1993). In the case of the TF-34, the RAP and NALDA database can be used to establish the current baseline performance using the MTBF, MTTR and A_i FOM's. These FOM's were selected due to their

interrelationship as shown by Equation (2), as well as their accepted status as measures of maintainability and reliability.

Once the distributions and their associated descriptive statistics have been established, selection of a benchmark value can be made using a specified upper percentile of the distribution function in the Time-To-Failure case, or a specified lower percentile of the distribution function in the Time-To-Repair case.

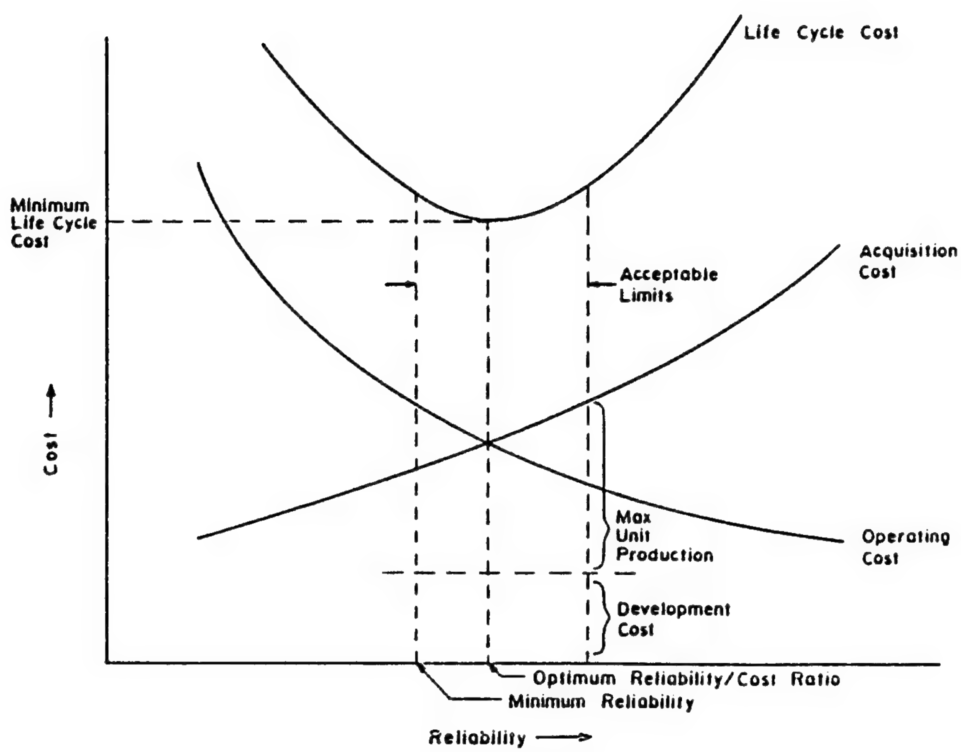

Figure 5. Cost versus reliability trade-off (From Ref. Anderson, March 1976).

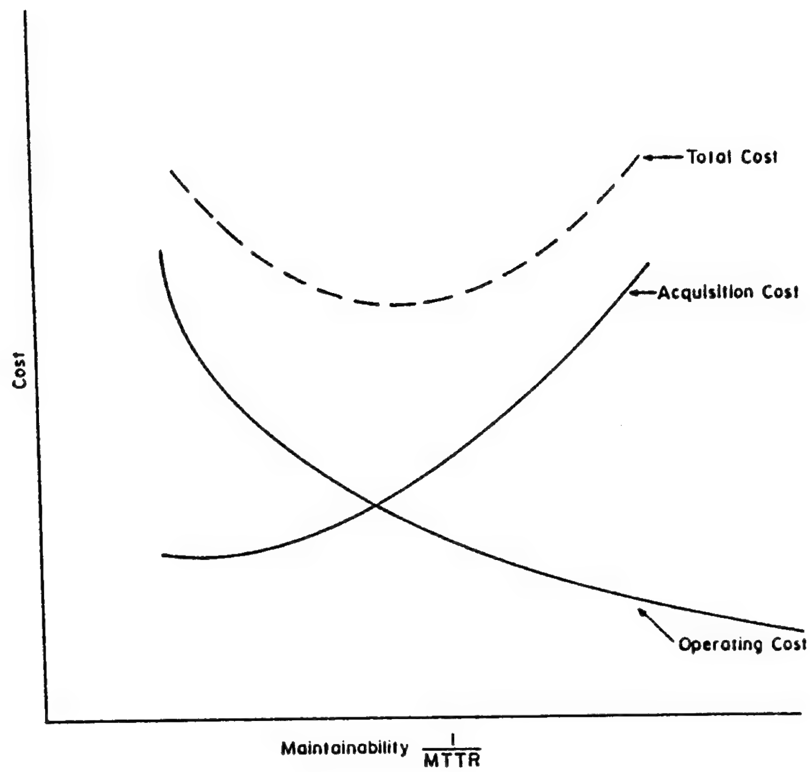

Figure 6. Cost versus maintainability trade-off (From Ref. Anderson, March 1976).

Using the distribution characteristics as a basis for selecting a benchmark value ensures that the value is at least a part of the distribution, as opposed to a point that is subjectively selected which may lie well outside the actual distribution. A point that lies outside the historical system cannot be met unless the incoming resources of the process are [modified] by management (Scherkenbach, 1988). For example, the Program Manager may select the 90th percentile of the

Time-To-Failure distribution, and the 30th percentile of the Time-To-Repair distribution as benchmark or target values for improvement. The A_i benchmark value can then be calculated directly from the MTBF and MTTR values.

In the case of the TF-34, the descriptive statistics table shown in Appendix A, Table I shows the MTBF (mean on wing time), as 570 hours. If a benchmark of 1000 hours MTBF is selected, Appendix B, Table III shows that, currently, only 15 percent of engines can be expected to remain "on wing" for 1000 hours. Therefore, some action must be taken in order to cause the reliability curve (Appendix B, Table III) to shift to the right, i.e. increase MTBF. It should be noted that regardless of how far the curve shifts, on average only 37 percent of the engines will ever reach the population MTBF value. This is due to the function that defines the negative exponential distribution. The MTBF value can be identified by the intersection between the 37 percent point on the reliability or "Y" axis , and the reliability curve itself. The MTBF lies below that intersection on the normalized time or "X" axis (Figure 7). (Note that "normalized time" is operating time divided by MTBF).

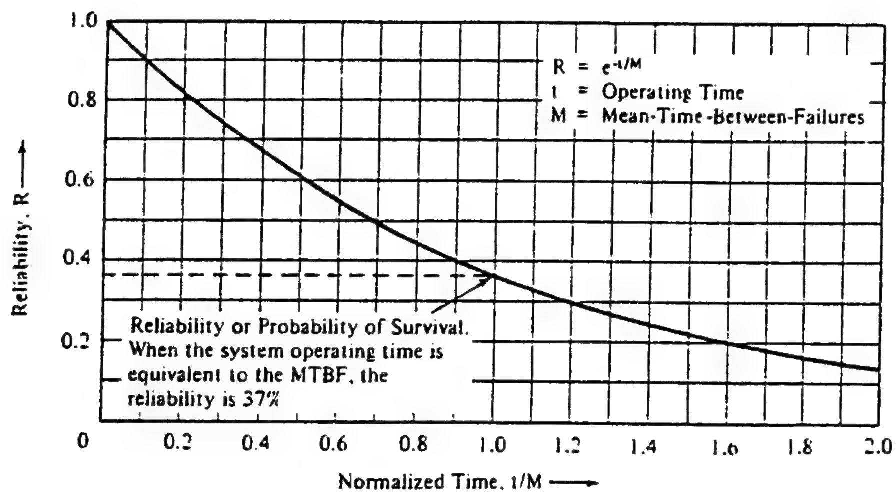

Figure 7. Exponential reliability function (From Ref. Blanchard, 1992).

Therefore, the current MTBF performance index is .56 or 56 percent of the benchmark "goal" (560/1000). This can also be interpreted as having another 44 percent to achieve.

It may be useful to establish a rate at which to achieve the desired benchmark value. This may be done by comparing the amount of MTBF improvement yet to be achieved, with the remaining intended useful life of the engine. For example, if the TF-34 remaining intended useful life is ten years, the steady state improvement in MTBF would ideally be achieved at the rate of 4.4 percent per year or 44 hours per year. This allows Program Managers and analysts to monitor the effect of component improvements on MTBF, and to gage the actual rate of MTBF improvement against the planned rate. Another criteria may base the rate of change on a predetermined cut-off point, after which further funding for improvements is no longer deemed economical, such as "remaining intended life minus 3 years."

C. CUMULATIVE DEGRADATION METHOD

1. Background

Mean time between mission affecting failures (MTBMAF), is one type of reliability parameter. It would seem desirable to set a goal for this parameter and strive to formulate maintenance policy to achieve the set goal. In this section, a model is discussed that can be used as one input for establishing aircraft engine maintenance policy that can help increase MTBMAF or engine reliability $\boldsymbol{RMA(t_0)}$. The model is introduced in a statistical setting and presumes the existence of some failure data which may be available in the NALDA data base or from accelerated testing programs. This data is

needed to establish stress-life curves. Such data or the curves themselves may have been established in development/validation testing programs or in other special testing programs. Alternatively, the curves themselves may have been developed in other research programs.

Using such stress-life curves, the cumulative degradation to an aircraft engine can be estimated. Knowing the number of operating hours at various levels of stress, this estimation procedure can be used to determine the operating time at which maintenance should be performed so that no more than 100 α percent of the engines will fail before maintenance is initiated.

The model provides the equation for deciding when to initiate maintenance. The decision rule for initiating maintenance on a specific engine takes into account the number of hours it was operated in each of several levels of stress. If there is significant wear-out in the engine between successive mission affecting failures, then it is more appropriate to set a goal for the associated engine reliability, $RMA(t_0)$. This is the probability that an engine will operate for more than t_0 hours since the last maintenance for mission affecting failures, for a given set of stress levels $S_1, S_2, \ldots, S_k$ and corresponding operating times $t_1, t_2, \ldots, t_k$ where:

$$\sum_{i=1}^{k} t_i = t_0 \tag{3}$$

The collection of $\{(S_1,t_1), (S_2,t_2), \ldots, (S_k,t_k)\}$ is called an operating environment scenario.

2. Cumulative Degradation Model

a. One Key Stress Factor

Numerous stress factors affect the operating time to failure of an aircraft engine. Examples of such factors are the following:

- Numbers of engine start-ups and aircraft takeoffs
- Temperature of engine during operations
- Preventive maintenance actions
- Quality of air intake (ingested)

In this section a method is presented for measuring the degraded life of an aircraft engine when it has operated at several levels of one stress factor for known times.

Suppose an engine is operated with all stress factors at nominal values except one factor, which is called the key stress factor. Let S_1, S_2, ... , S_k be the k different levels of this stress factor. These stress levels may be categorical (e.g., high, medium, low), or they may be numerical. Suppose the operating time to failure, TS_i, of an engine operating at stress level S_i has some probability distribution. Suppose the 100 α percentile point $t(\alpha)_i$, of this probability distribution has been estimated for each stress level where α is some given value in (0,1). That is, $P(TS_i \geq t(\alpha)_i)=1-\alpha$ for i=1, 2, . . . , k. The term $t(\alpha)_i$ represents the allowed degradable life under stress S_i. The quantity 100α% is the largest percentage of unscheduled failures deemed acceptable. For example, α=.30 means that the goal for unscheduled failures due to this key stress factor has been set at 30 percent. The following procedure can be used to facilitate assurance that this goal will be met:

a.) If the engine operates at key stress level S_i for

t_i units of time, it will have used up $t_i/t(\alpha)_i$ proportion of its allowed degradable life at this stress level S_i, where $i = 1, 2, \ldots, k$.

b.) The engine is scheduled for maintenance due to the key stress factor whenever the allowed degradation of its life is depleted as given by Equation (4).

$$\sum_{i=1}^{k} \frac{t_i}{t(\alpha)_i} = 1 \qquad \textbf{(4)}$$

If this maintenance policy is followed, then the percentage of maintenance actions for this stress factor, due to unscheduled engine failures caused by this key stress factor, should be approximately α percent.

Numerous standard statistical methods are available to estimate the percentile points $t(\alpha)_i$ depending on the data available and assumptions about the probability distributions of the TS_i variables. Existing data sources need to be reviewed in order to select the appropriate methods to estimate the $t(\alpha)_i$. This could be an effort for future research.

Example: An aircraft engine has three categories of operating temperature, low (1), medium (2), and high (3). The MTBF of the engine depends upon how much operating time is expended in each temperature category. Suppose that about 20 percent of unscheduled maintenance due to operating temperature is considered acceptable. Suppose estimation of the $t(.20)_1$, $t(.20)_2$, and $t(.20)_3$, have been obtained and

$$t(.20)_1 = 800 \text{ hours}$$
$$t(.20)_2 = 600 \text{ hours}$$
$$t(.20)_3 = 250 \text{ hours}$$

For a given mission environment the engine will operate at

high temperature level 20 percent of the time, at medium temperature level 70 percent of the time, and at low temperature level 10 percent of the time. If T_o is the total operating time before scheduled maintenance, then T_o can be found from the equation:

$$.2T_o/250 + .7T_o/600 + .1T_o/800 = 1$$

That is, T_o = 478 hours. Consequently, if the engine is operated in a manner indicated by the distribution of 20%, 70%, 10% to the temperature stress levels, and if maintenance is scheduled for approximately every 500 hours, then, approximately 20% of the engines will require unscheduled maintenance due to temperature stress.

Alternatively, if each engine is scheduled for maintenance whenever

$$t_1/800 + t_2/600 + t_3/250 = 1$$

where t_i = operating time at temperature level i, then about 20 percent of the engines will require unscheduled maintenance. The concept of an engine using $t_i/t(\alpha)_i$ of its allowed degradable life is a variation of a method used by engineers in analysis of *S-N* curves. The rule as given by Equation (4), which corresponds to the expenditure of all allowed degradable life, is known as Miner's Rule (Miner, 1945).

b. Several Additive Key Stress Factors Acting Simultaneously

Suppose J key stress factors can be applied to an engine simultaneously, let the vector $\underline{i} = (i_1, i_2, \ldots, i_J)$ denote the

combined stress levels acting simultaneously on an engine where the element i_j denotes the stress level for stress factor J. That if there are three key factors each with two stress levels, then the vector (2,1,3) denotes stress level 2 for factor 1, stress level 1 for factor 2 and stress level 3 for factor 3. let $t[\alpha;(i_1, i_2,...,i_j)] \equiv t(\alpha\underline{i})$ be the 100α percentile of the time to failure of an engine when the J stress factors are operating simultaneously on the engine at levels $(i_1, i_2,...,i_j)$. Let V_j denote the set of all actual combinations of simultaneously acting stress levels on an engine. If preventive maintenance is performed on an engine when the conditions illustrated in Equation (5) have been met,

$$\sum_{\underline{i}\in V_J} \frac{t(\underline{i})}{t(\alpha;\underline{i})} = 1 \qquad \textbf{(5)}$$

then approximately, $100\,\alpha$ percent of the engines would fail before preventive maintenance is performed.

Suppose operating temperature (1) and air intake pollution (2) are the two key stress factors affecting the lifetime of an engine. Temperature levels are low (1), medium (2), and high (3) and two levels of air pollution; low (1), and high (2). Suppose all combinations of these two stress factors are possible on an engine, then J=2 and $V_2 = \{(i_1, i_2); i_1 = 1,2,3,\ i_2 = 1,2...\}$. V_2 has 6 vector elements. Suppose estimates of the 30th percentile points, $t[\alpha;(i_1,i_2)]$ Time-To Failure $T(i_1,i_2)$ of an engine operating continuously at combined stress levels (i_1,i_2) have been obtained.

t[30;(1,1)]=900
t[30;(1,2)]=750
t[30;(2,1)]=600
t[30;(2,2)]=450
t[30;(3,1)]=400
t[30;(3,2)]=100

Let $t(i_1,i_2)$ denote the accumulated operating time on an engine at stress levels $t(i_1,i_2)$. If preventive maintenance is scheduled on an engine when:

$$\frac{t(1,1)}{900}+\frac{t(1,2)}{750}+\frac{t(2,1)}{600}+\frac{t(2,2)}{450}+\frac{t(3,1)}{400}+\frac{t(3,2)}{100}=1$$

Then approximately 30% of the engines will fail prior to preventive maintenance. If estimates , $p(i_1,i_2)$, of the proportion of the time, an engine will operation at stress level (i_1,i_2) are known then the scheduled preventive maintenance time, T_o, for this engine could be determined by solving for T_o in the equation:

$$\frac{p(1,1)\,T_o}{900}+\frac{p(1,2)\,T_o}{750}+\frac{p(2,1)\,T_o}{600}+\frac{p(2,2)\,T_o}{450}+\frac{p(3,1)\,T_o}{400}+\frac{p(3,2)\,T_o}{100}=1$$

If all engines are scheduled for preventive maintenance to operating hours, then approximately 30% of the engines would fail before preventive maintenance was performed.

IV. CONTINUOUS PROCESS IMPROVEMENT

Reliability and maintainability trade study analysis on the critical few Pareto items will provide the path to project by project improvement in maintainability and reliability factors. The Pareto principle suggests the use of the high five failure items or abort items, as the focal point for achieving the greatest amount of system reliability and maintainability improvement per dollar expended. However, once the critical few have been identified, the question remains as how best to allocate resources to these five items to obtain the greatest increase in reliability (maintainability) for the dollar resources available. This problem is a trade-off analysis problem. Existing reliability allocation optimization software tools may be useful in solving this problem. If approximate reliability (maintainability) improvement cost functions can be developed for each critical item, then existing software can be used to optimize reliability improvement. A Failure Verification Analysis and Corrective Action effort will be required for each of the identified critical items to determine possible corrective actions and associated costs. Some corrective actions may only involve modification in the way the aircraft is flown. Use of these methods using the Control Program For Engineering Synthesis (COPES) is recommended as a topic for future research (Madsen, March 1982).

The cause of these failures must be investigated depending on the failure modes discovered. Most of this data will normally be recorded at the manufacturers overhaul facility, or at the intermediate and depot levels of maintenance within the Navy. If the depot level data indicates the primary cause of a components failure is due to inadequate lubrication of a particular bearing, for example, the investigative process has just moved another step closer to a solution. Another

iteration begins with the question, why is the lubrication inadequate? Again, the seven primary areas to look are: management, maintenance, materials, methods, machines, measures and manpower. This iterative process repeats itself at each level, system, subsystem, component, subcomponent, until the root cause is identified. Only then can alternative courses of action be evaluated.

The implication is that the greatest amount of maintainability or reliability improvement per dollar expended (marginal gain) will be achieved by performing a cost trade-off type analysis on the critical few Pareto items. Once this has been accomplished, a new list of high five components is generated and the improvement process is repeated. This is Continuous Process Improvement at work.

V. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

A. SUMMARY

The following topics are covered in this thesis:

- Selection of objective logistics performance measures known as Figures of Merit (FOM)
- Demonstration of a procedure for establishing current fielded jet engine logistics performance
- Discussion of a standardized method for comparison of existing logistics performance with original specifications or with a benchmark value, referred to as a Performance Index
- Discussion of the Cumulative Degradation Method of reliability analysis
- Discussion of a recommended procedure for calculating benchmark FOM values from statistical distributions when original design values are not available
- Demonstration of commercially available spreadsheet software (EXCEL) to develop statistical distributions using NALDA and RAP data
- Discussion of the Pareto principle and Continuous Process Improvement (CPI) as a structured approach to improving fielded jet engine reliability and maintainability

B. CONCLUSIONS

The NALDA database is currently difficult to access and query. The RAP users manual discusses the downloading and interpretation of data as a measure of days. This seems excessive based upon current DBMS technology.

The Reliability Analysis Reports are an excellent source of information, applicable primarily to Program Managers in monitoring the macro view of fielded jet engine logistics performance. The analyst may find interactive manipulation of the NALDA database more useful as compared with the standard

RAP reports.

Most organizational level logistics information is not currently measured or analyzed in the RAP reports. The data necessary to conduct organizational level analysis should be available through NALDA, but may be difficult to analyze with the current DBMS. To do so more effectively and efficiently requires improving the DBMS, and the variety of statistical and spreadsheet software options available to the analyst.

Each of the methods and procedures discussed in this thesis uses relatively simple statistical techniques combined with commercially available spreadsheet software programs. Application of these methods and procedures will allow Program Managers and Data Analysts to compare fielded jet engine logistics performance against common, easily calculated criteria. Once the FOM values have been selected and calculated, they will provide quantifiable indications of the effectiveness of any changes made in attempts to enhance system reliability and maintainability.

C. RECOMMENDATIONS

- Determine which logistics performance parameters (FOM values) are to be computed by the Data Analyst on a regular basis. Build an FOM sub-database, separate from the current NALDA database, that will contain only those elements necessary for the calculations of the chosen FOM values. This should make data access easier, faster and more efficient than the current NALDA data query method since this FOM sub-database will be much smaller and more specialized. The sub-database could be updated from the NALDA database via NAMO or other designated manager. This will make data accessible without being a NALDA expert.

- Computation of logistics performance FOM values must include organizational level maintenance data, in addition to intermediate and depot level data. Currently, organizational level logistics performance evaluation and analysis is not emphasized in the RAP

reports, yet this is where the focus for improving system reliability and maintainability should be, i.e., at the operator (customer) level.

- Tools and methods for analysis of the data available through NALDA, should not be limited to the standard RAP reports. Data Analysts should have the flexibility to conduct interactive, real time analysis of any database parameters chosen. The RAP report serves as an excellent overall monitoring tool, but is limited in its usefulness as a tool for logistics performance analysis of fielded jet engines.

- The NALDA database management system (DBMS) should be updated to meet industry standards. The use of CD-ROM storage, icons, windows, high speed modems, access to data via MILNET/INTERNET and other management information systems are essential for a viable logistics management program. A cost/benefit analysis based on industry examples would be useful in justifying the initial investment required.

- Take advantage of the expertise offered by the Society of Logistics Engineers. They have a program to provide, free of charge, services to assist in the resolution of logistics related challenges. Their services are available to all government agencies, and would be ideal for providing an analysis of the current NALDA DBMS, at no cost to the government.

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APPENDIX A. TIME-TO-FAILURE DISTRIBUTION

(Refer to Table I).

Life-In-Hours: This column is generated by the spreadsheet software program (EXCEL in this case) and divides the Life-In-Hours data into equal range bins or intervals of time.

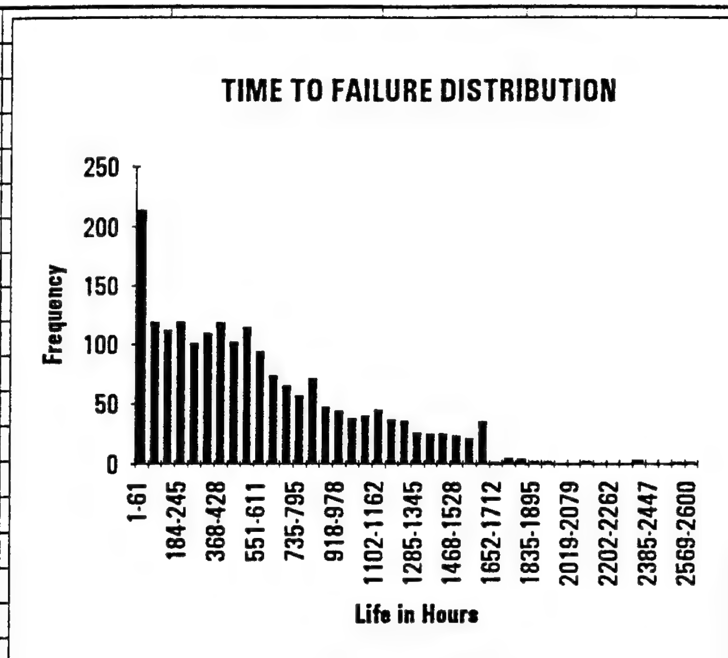
Frequency: This is a count of how many data points fall into the associated range bin. The first entry in this case is 214 Time-To-Failure data points that fall into the 1 to 61 Life-In-Hours range bin.

Cumulative Percentage: This column measures what cumulative percentage of the engines have failed (unscheduled removal) within the associated Life-In-Hours range bin. Again, the first row of data indicates that 214 of the total 1932 Time-To-Failure data points provided by the NALDA query, fall into the 1 to 61 hour range bin, or 11.08 percent of the total (214/1932).

Interpretation: Take for example, the Life-In-Hours range bin of 490 to 550 hours. Reading across this row of data indicates that there were 114 cases where TF-34 engines were removed from an aircraft after surviving between 490 to 550 hours installed. Continuing across the row, 57.35 percent of TF-34 engines have failed (unscheduled removal) within 550 hours of operating time. This same information is portrayed graphically along with a descriptive statistics table. The graph makes it very easy to identify the exponential failure distribution.

Note: Time-To-Failure in this case measures how long TF-34 engines remain on-wing before unscheduled removal for maintenance at the intermediate or depot level of repair.

Life in Hours	Frequency	Cumulative %
1-61	214	11.08%
62-122	119	17.24%
123-183	112	23.03%
184-245	119	29.19%
246-306	101	34.42%
307-367	109	40.06%
368-428	118	46.17%
429-489	102	51.45%
490-550	114	57.35%
551-611	94	62.22%
612-673	74	66.05%
674-734	65	69.41%
735-795	57	72.36%
796-856	71	76.04%
857-917	47	78.47%
918-978	44	80.75%
979-1039	38	82.71%
1040-1101	40	84.78%
1102-1162	45	87.11%
1163-1223	37	89.03%
1224-1284	36	90.89%
1285-1345	26	92.24%
1346-1407	25	93.53%
1407-1467	25	94.82%
1468-1528	23	96.01%
1529-1590	21	97.10%
1591-1651	35	98.91%
1652-1712	1	98.96%
1713-1773	5	99.22%
1774-1834	4	99.43%
1835-1895	2	99.53%
1896-1956	2	99.64%
1957-2018	0	99.64%
2019-2079	0	99.64%
2080-2140	2	99.74%
2141-2201	0	99.74%
2202-2262	0	99.74%
2263-2323	0	99.74%
2324-2384	3	99.90%
2385-2447	0	99.90%
2448-2507	0	99.90%
2508-2568	1	99.95%
2569-2600	1	100.00%



Statistics	*Time to Failure*
Mean (MTBF)	569.9699793
Standard Error	10.34205607
Median	474.5
Mode	1
Standard Deviation	454.5801303
Variance	206643.0949
Kurtosis	0.33845718
Skewness	0.894929934
Range	2629
Minimum	1
Maximum	2630
Sum	1101182
Count	1932

Table I. TIME TO FAILURE DISTRIBUTION AND DESCRIPTIVE STATISTICS

APPENDIX B. RELIABILITY FUNCTION

(Refer to Table II)

Life-In-Hours and Number-Of-Failures: See Appendix A, Time-To-Failure distribution explanation.

Failure Rate: This column measures the number of failures (unscheduled removals) occurring for the associated Life-In-Hours range bin, divided by the total hours of engine operating time accumulated among all engines.

Units Surviving: This measures how many engines (data points) are still operating of the total number in the population or sample. This number does not match the total number of TF-34 engines in the inventory because the data points were taken from five years worth of NALDA information. Therefore many of the data points apply to the same engines over time.

Reliability: This is a measure of how what percentage of engines (data points) are still operational (on-wing) of the total population or sample.

Interpretation: Take for example the Life-In-Hours range bin of 490 to 550 hours. Reading across, the number of failures occurring in this range bin is 114. The associated Failure Rate column indicates .00196 failures per hour of operating time for engines surviving between 490 to 550 hours. This equates to 1.96 failures per 1000 hours, or approximately 1 unscheduled removal, on average, for those engines that reach the 490-550 hour range bin (550 X .00196). The Units Surviving column indicates 824 engines are still on-wing, which equates to the Reliability column 42.65 percent (824/1932).

Life in Hours	# of Failures	Failure Rate	Units Surviving	Reliability
1-61	214	0.001786549	1718	88.92%
62-122	119	0.001117203	1599	82.76%
123-183	112	0.001129738	1487	76.97%
184-245	119	0.001290756	1368	70.81%
246-306	101	0.001190813	1267	65.58%
307-367	109	0.001387581	1158	59.94%
368-428	118	0.001643546	1040	53.83%
429-489	102	0.001581886	938	48.55%
490-550	114	0.001960245	824	42.65%
551-611	94	0.001839962	730	37.78%
612-673	74	0.001634998	656	33.95%
674-734	65	0.001598151	591	30.59%
735-795	57	0.001555592	534	27.64%
796-856	71	0.002144497	463	23.96%
857-917	47	0.001637288	416	21.53%
918-978	44	0.001705955	372	19.25%
979-1039	38	0.001647589	334	17.29%
1040-1101	40	0.001931621	294	15.22%
1102-1162	45	0.002468729	249	12.89%
1163-1223	37	0.002396684	212	10.97%
1224-1284	36	0.002738892	176	9.11%
1285-1345	26	0.002382698	150	7.76%
1346-1407	25	0.002688172	125	6.47%
1407-1467	25	0.003225806	100	5.18%
1468-1528	23	0.003709677	77	3.99%
1529-1590	21	0.004398827	56	2.90%
1591-1651	35	0.010080645	21	1.09%
1652-1712	1	0.000768049	20	1.04%
1713-1773	5	0.004032258	15	0.78%
1774-1834	4	0.004301075	11	0.57%
1835-1895	2	0.002932551	9	0.47%
1896-1956	2	0.003584229	7	0.36%
1957-2018	0	0	7	0.36%
2019-2079	0	0	7	0.36%
2080-2140	2	0.004608295	5	0.26%
2141-2201	0	0	5	0.26%
2202-2262	0	0	5	0.26%
2263-2323	0	0	5	0.26%
2324-2384	3	0.009677419	2	0.10%
2385-2447	0	0	2	0.10%
2448-2507	0	0	2	0.10%
2508-2568	1	0.008064516	1	0.05%
2569-2600	1	0.016129032	0	0.00%

Table II. TIME-TO-FAILURE SPREADSHEET DATA

Failure Rate and Reliability Function Graphs

(Refer to Table III)

The Failure-Rate-Function graph displays the Failure Rate versus the Life-In-Hours. The data is taken directly off of the Reliability Function data table explained previously. The importance of this graph is that it verifies the relatively constant failure rate (unscheduled removals) that is defined by the exponential failure rate function as given by Equation (4).

From this graph it is clear to see that engines tend to experience a stable failure rate (unscheduled removal rate) of approximately .002 per hour or 2 per 1000 hours, out to approximately the 1300 hour mark. Thereafter, failures (removals) are typically associated with component wear-out.

The Reliability Function Graph displays Percent Reliability versus Life-In-Hours and is also taken directly from the Reliability Function data table. Since this graph is measuring reliability (vice failures) it's slope is negative while that of the Failure Rate Function graph is zero followed by positive slope. The Reliability graph is also smoothed due to the use of percentages. This graph indicates once again that the relationship between Life-In-Hours and reliability is indicative of the exponential reliability function. Reading across and down, at the 37 percent reliability level, the expected life in hours is approximately 560 hours. This is consistent with the MTBF calculation on page 1, Appendix A.

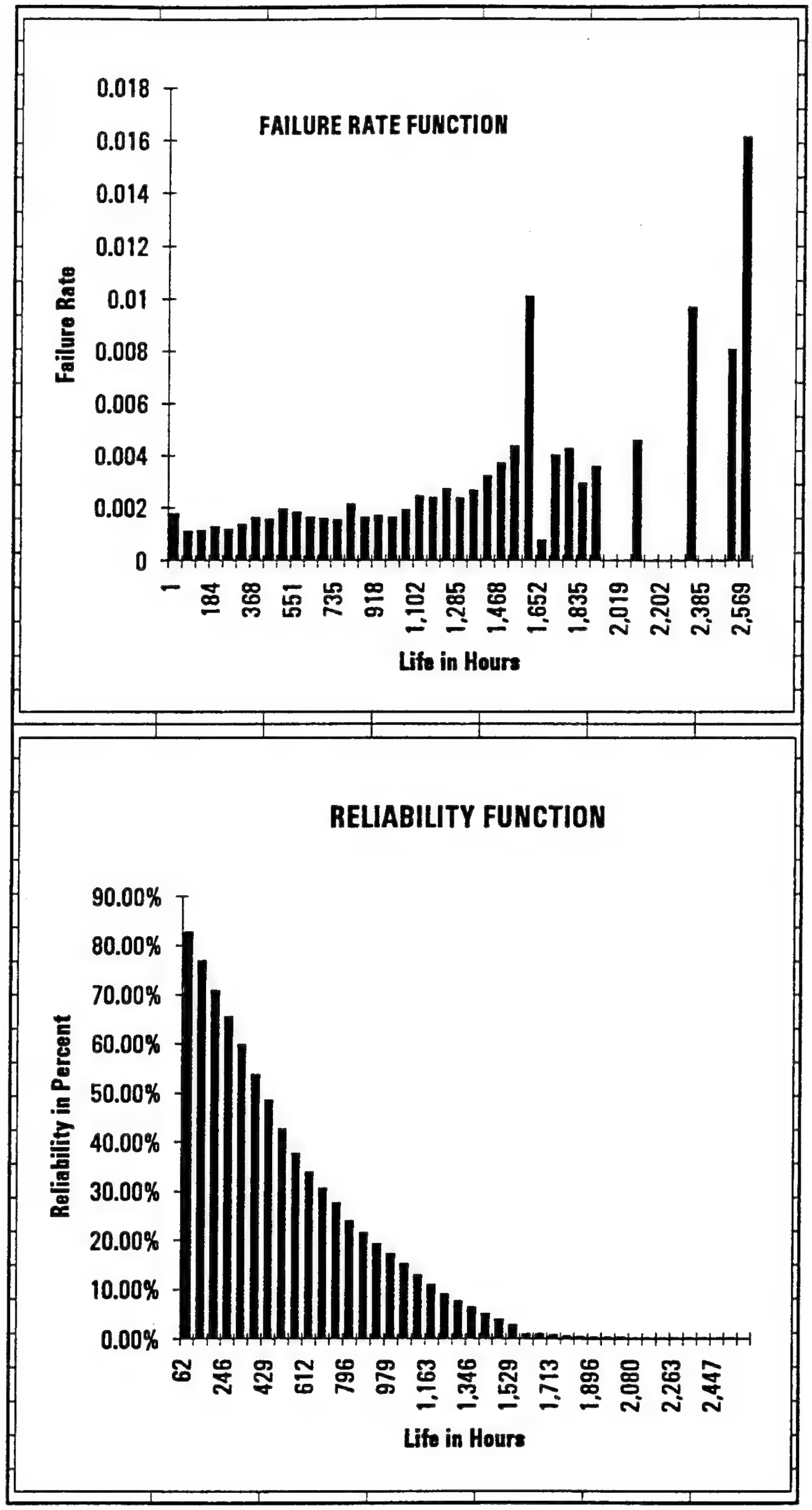


Table III. FAILURE RATE AND RELIABILITY FUNCTION GRAPHS

APPENDIX C. TIME-TO-REPAIR DISTRIBUTION

(Refer to Table IV)

Days: This column contains the range bins that divided into equal intervals of time.

Frequency: This column is a count of how many repair actions fell into the associated Days range bin.

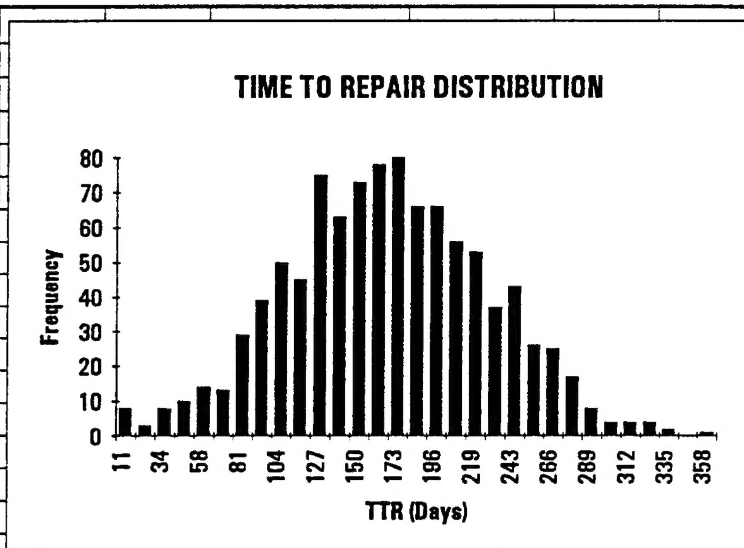
Cumulative Percent: This column is a measure of the cumulative number of repair actions that fell into the associated days range bin, divided by the total number of repair action data points retrieved from the NALDA query.

Interpretation: Take for example the 93 to 104 Days range bin. Reading across the row, there were 50 data points (repair actions) out of the total population or sample, that required between 93 and 104 days to complete. In the case of the TF-34 data, this is actually a measure of how long the engine remained in the repair pipeline at the intermediate or depot level of maintenance before it was installed on an aircraft again. The sum of all repair actions up to the 104 day mark, divided by the total number of repair actions (data points) retrieved from NALDA, yields the cumulative percent of 17.4 (174/1000).

The Graph indicates a Normal distribution, which is expected.

Note: The MTTR data used in this thesis was approximated based upon a very small data sample taken from the October 1993 RAP report, and was used only for the purpose of demonstrating the MTTR distribution methodology. Actual Time-To-Repair data points are available through NALDA.

Days	Frequency	Cumulative %
11	8	0.80%
23	3	1.10%
34	8	1.90%
46	10	2.90%
58	14	4.30%
69	13	5.60%
81	29	8.50%
92	39	12.40%
104	50	17.40%
115	45	21.90%
127	75	29.40%
138	63	35.70%
150	73	43.00%
162	78	50.80%
173	80	58.80%
185	66	65.40%
196	66	72.00%
208	56	77.60%
219	53	82.90%
231	37	86.60%
243	43	90.90%
254	26	93.50%
266	25	96.00%
277	17	97.70%
289	8	98.50%
300	4	98.90%
312	4	99.30%
324	4	99.70%
335	2	99.90%
347	0	99.90%
358	1	100.00%



Statistics	Time to repair
Mean (MTTR)	172.8767859
Standard Error	1.89631174
Median	172.5255401
Mode	65.90835253
Standard Deviation	59.96664253
Variance	3595.998216
Kurtosis	-0.161512243
Skewness	0.029969259
Range	358.5897502
Minimum	11.24062694
Maximum	369.8303771
Sum	172876.7859
Count	1000

Table IV. TIME TO REPAIR DISTRIBUTION DATA AND GRAPH

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